Faculty of Technology

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Information Technology

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Contents	Page No.
1. Introduction	3
2. Literature review	5
2.1 Research Gaps	9
3. Objectives	10
4. Methodology	11
5. Scope of research	15
6. Hypothesis	17
7. Summary	18
8. Future Scope	19
9. References	20

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Certificate

This is to certify that the Ph.D topic approval presentation by **Ms.Deepali Shrikhande** on **"Precise Decision Support System for MultiCrop-MultiDisease Detection"** has been approved and the report for the same is being submitted herewith.

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1. Introduction:

In today's world, agriculture plays a crucial role in the economic development of many countries. However, the increasing demand for food due to a growing population has put pressure on farmers to increase their crop yield while minimizing losses caused by various diseases.

The traditional methods of disease detection, such as visual inspection and manual diagnosis, are time-consuming, subjective, and often unreliable. Crop diseases can cause significant losses to farmers, affecting their livelihood and the economy as a whole. Crop disease detection systems can assist farmers in identifying the diseases affecting their crops, allowing them to take appropriate action to mitigate the damage. Therefore, there is a need for an automated system that can quickly and accurately detect multiple diseases in multiple crops.

A Precise Decision Support System is a software-based tool that helps users make well-informed decisions by providing them with accurate and relevant information. It uses advanced analytical techniques to process large amounts of data from various sources and produce actionable insights. A precise decision support system in digital agriculture refers to a set of technologies and tools that enable farmers and agricultural professionals to make data-driven decisions about crop management.[1]

A precise decision support system for crop disease detection uses advanced techniques such as machine learning, computer vision, and data analytics to accurately identify and classify diseases in crops. This system enables farmers to take proactive measures to protect their crops, increase yield, and reduce the spread of disease.

The Precise Decision Support system for MultiCrop-MultiDisease Detection is a machine learning-based system that aims to detect multiple diseases in multiple crops. The system uses image processing and Machine learning, deep learning algorithms to analyze the images of the crops and identify any diseases present. Research in Precise Decision Support systems for crop disease detection is crucial for sustainable agriculture. These systems can accurately and quickly detect diseases, allowing for timely interventions and reducing crop losses.

It is an innovative and intelligent solution that leverages advanced technologies such as machine learning, image processing, and computer vision to help farmers detect multiple diseases across multiple crops accurately. The system is designed to provide real-time and precise

recommendations to farmers, enabling them to take proactive measures to control and prevent diseases in their crops, thus reducing losses and improving yields.[3]

The Precise Decision Support system for MultiCrop-MultiDisease Detection has the potential to revolutionize the agricultural industry by providing a quick and accurate means of disease detection in multiple crops reducing crop losses, and optimizing the use of resources. This system can help farmers to increase their crop yield, minimize losses caused by diseases, and ultimately contribute to the economic development of their respective countries. Research in this field is essential to develop effective and scalable solutions that can meet the needs of farmers and support sustainable agricultural practices.

2. Literature Review:

- Various algorithms are seen in machine learning and deep learning for disease diagnosis in 2020, according to Wani, J.A. [1]. In terms of deep learning approaches, CNN performs well. Also, ML allows for the implementation of chemical and pesticide recommendations based on the detected disease. SVM performs well. There are four sorts of crops taken into account: tomato, rice, potato, and apple.
- M. Alencastre-Miranda, R. M. Johnson, and H. I. Krebs[2] introduced a convolutional neural network (CNN) and transfer learning approach for quality inspection of various sugarcane types in paper. In order to train a CNN model, the authors gathered a dataset of 13,000 photos of sugarcane leaves from five different types. Four convolutional layers made up the CNN design, which was then followed by two fully connected layers and a SoftMax output layer. The findings demonstrated that the suggested method successfully classified the sugarcane leaves into their respective kinds with an accuracy of 99.2%.
- Sakkarvarthi, G.Sathianesan, G.W. Murugan, V.S.[3] in 2022 ,Sakkarvarthi et al. (2022) proposed a system for detecting and classifying tomato crop diseases using Convolutional Neural Networks (CNNs). The authors collected a dataset of tomato plant images with different diseases and healthy plants. They trained and evaluated the performance of three different CNN architectures using the collected dataset. The findings demonstrated that the suggested method detected and classified illnesses of tomato crops with a training accuracy of 98%. The suggested technique might be effective for keeping an eye on tomato plant health and reducing disease-related crop losses.
- Geetharamani G., Arun Pandian J.,[4] The suggested Deep CNN model can effectively classify 38 unique types of healthy and unhealthy plants using leaf photos in 2019. The suggested model produces an average result. The suggested model achieves an accuracy of 96.46% on average. An continuation of this research will involve gathering fresh photographs of various plant species, image characteristics, etc. from other sources in order to expand the database's class structure and data size. It is possible to expand work from plant leaves to other plant parts like flowers, fruits, and stems.
- Selvaraj, M.G., Vergara, A., Ruiz[5] in 2019 ,Dataset used consists of images collected from Africa and South India. Size of the dataset is 18k.Images at different growing phases of the

crop are taken in a dataset.Cnn was used in this. Development of server side consisting of trained models and an app.Taking aerial image using drones and instant segmentation of disease.

- Ahmed, A.A., and Reddy, G.H.[6] took 96000 datasets in 2021. For identifying 38 disease types, the created system uses Convolutional Neural Networks (CNN) as the underlying deep learning engine. To train, validate, and test the CNN model, we gathered pictures of healthy and diseased plant leaves. The only places this model is usable are states. Plants should be photographed properly because they can contain fictitious date settings. It is possible to add more kinds of plants and veggies.
- V. Pallagani, V. Khandelwal, B. Chandra, V. [7] in 2019 ,A deep convolutional neural network algorithm is used in this paper. The trained model has achieved an accuracy of 99.24% and can identify 14 crop species and 26 diseases.The app can be made to work in different regional languages for ease of use by the farmer.Dataset used consists of only 54,000 images to improve the efficiency a bigger database of different crops can be used.
- Kabir, M.M., Ohi, A.Q., and Mridha [8] developed a reliable and practical method for multi-plant disease diagnosis using CNN in 2021. 10,000 photos of healthy and damaged plant leaves were gathered by the authors from various locations in Bangladesh. The preprocessed, enhanced, and divided dataset was used to create training and testing sets. The suggested strategy, which might be used to other crops as well, yielded encouraging results in the detection and diagnosis of illnesses in tomato, potato, and eggplant.
- Roy, Arunabha M., and Jayabrata Bhaduri [9] in 2021,Different ML methods, like as K-means clustering and support vector machine (SVM), have been used for plant and disease categorization. Due to their increased accuracy in object detection, convolution neural network (CNN)-based models have become significantly more popular. By automatically extracting features straight from the input images, CNNs can eliminate laborious preprocessing. Faster R-CNNs use region proposal networks (RPNs) and classification networks to significantly reduce detection times, but they are unable to detect objects in high-resolution images in real time. .however, these techniques perform less well and more gradually in real-time illness detection because of the difficult picture preprocessing and feature extraction stages.

- Konstantinos P. Ferentinos,[10] in 2018 ,VGG convolutional neural network was implemented which gave very high accuracy (99.53%). Databases used were very common and easily available. The same model can be implemented using some real images.
- In the 2017 NextGen Special Issue, John M. Antle, James W. Jones, and Cynthia Rosenzweig[11] The strategy is to advance data, models, and knowledge products that align with the goal by combining knowledge and developing a plan. Addressing important use cases and meeting end-users' needs will shift towards a more demand-driven approach from the existing supply-driven one.
- Alexis Joly, Sue Han Lee, Hervé Goau, and Pierre Bonnet[12] in 2020 , To maintain sustainable agriculture and global food security, controlling plant diseases is a serious challenge. Recent studies have shown ways to enhance current methods for early disease detection in plants using cutting-edge deep learning-based automatic image recognition systems. established a more user-friendly strategy that takes illnesses into account separately from crops, and we demonstrate that it is superior to the traditional crop-disease pair approach, particularly when dealing with diseases involving crops that are not represented in the training database. This result therefore encourages further research to reconsider the existing paradigm for categorizing plant disease.
- In 2020, Zhaoyu Zhai, José Fernán Martnez, [13], A thorough analysis of the most recent agricultural decision-support tools for Agriculture 4.0 has been offered in this research. 13 ADSSs have been identified from recent articles and projects. These ADSSs are examined in terms of their data sources, scheduling tools, systems for decision support produced, problems that were addressed, and supporting periods. Issues highlight potential improvements for researchers and future development patterns of using ADSSs in agriculture 4.0. It is encouraging to see that by addressing these obstacles, future ADSSs can better serve Agriculture 4.0.
- In 2022, Julie Ingram, Damian Maye, and Clive Bailye [14] There were 27 priority questions in total, distributed over 7 research themes (15 gold, 7 silver, and 5 bronze). Exercises in prioritisation provide a rigorous interactive process for gathering and arranging a variety of viewpoints. The approach is in accordance with proposals for new types of institutional, legal, and scientific governance, as described in frameworks for responsible

research and innovation (RRI), where the approach calls for increasing focus on issues of anticipation, inclusion, reflexivity, and responsiveness

- In 2021, Markus Zanker[15], Gabriele Sottocornola, Sanja Baric, Maximilian Nocker, Fabio Stella The suggested method is easily adaptable and extendable to related fields where a user's dynamic interaction with an image-based knowledge base can be utilised to aid in disease diagnosis. The key unresolved issue for the system's future development is to the addition of structured domain experts to DSS Apple's reasoning engine.
- In 2022, Kamran Munir, Mubeen Ghafoor, Mohamed Khafagy, and Hisham Ihshaish[16] Data from the agriculture sector can be both historical and process-related. Processing and analyzing historical and process-related data from the agriculture sector is challenging and involves critical decisions such as selecting data storage based on data nature and modality. The vast amounts of agricultural data collected have the potential to enhance decision-making for farmers and governments. The future of agriculture lies in adopting big data technologies and smart farming practices.
- Meselu Tegenie Mellaku and Ashebir Sidelil Sebsibe[17] in 2022, Research suggests that using multi-objective mathematical models with GIS is a more realistic approach to agricultural decision-making and encourages a systemic method for making decisions. Incorporating mathematical model-based decision-making in land use planning and agriculture in developing countries can significantly enhance agricultural production efficiency and help eradicate poverty amidst climate change.
- In 2019, Evan D.G. Fraser and Malcolm Campbell [18] The challenges faced by humanity in the twenty-first century require a new agricultural revolution that utilizes technology to increase output while maintaining environmental sustainability. Research must focus on interdisciplinary, cost-effective, and ecologically efficient food and farming systems. Ethnically, economically, and politically appropriate application of these insights is crucial for effective food production and distribution.
- Qiao Jie [19] in 2022 , This article utilizes big data technology to mine and optimize agricultural data, improving decision-making and economic development. The decision support system uses accurate processing to make predictions and scientific decisions, enhancing the effectiveness of agricultural production structure.

- Weckesser, F.; Beck, M.; Hülsbergen, K.-J.; Peisl, S.[20] in 2022 By integrating data from various sources, farmers and advisors can easily access crop information for each field. The knowledge base includes farm, field, soil, and climate data, as well as rules, facts, and guideline values. This enables the system to automatically generate recommendations for farmers. By providing smart tools that support analysis, evaluation, optimization, scenario simulation, and output of recommendations, the system addresses the need for advanced tools to assist farmers.

2.1 Research Gap:

Despite the numerous benefits of precise decision support systems for multi crop multi disease detection, there are still some research gaps in this area that need to be addressed. One of the major challenges is the lack of standardization in the collection and annotation of image datasets. The accuracy of machine learning algorithms heavily relies on the quality and quantity of data used to train them. Hence, it is crucial to have standardized image datasets that cover a wide range of crops and diseases to improve the accuracy and generalizability of these algorithms.

Another research gap is the limited availability of open-source software tools for multi crop multi disease detection. While several commercial software solutions exist, they are often expensive and may not be affordable for small-scale farmers.

Moreover, most of the research in this area has focused on the technical aspects of developing machine learning algorithms for disease detection. However, there is a need for more research on the practical implementation of these systems in real-world farming scenarios. Farmers need to be educated on the benefits of these systems and trained on how to use them effectively to maximize their impact.

While these systems can improve productivity and reduce crop loss, they also require significant investment in terms of software, and training. Therefore, more studies are needed to evaluate the cost-effectiveness of these systems and their potential return on investment for farmers for precise decision making about crop management.

3. Objectives of the Research:

• To develop a knowledge base for precise and reliable decision making in crop MultiDisease detection (Phases of data collection and data formulation) for implementing reliable and effective crop MultiDisease detection solutions.

• To investigate and improve the efficacy of a decision support approach for detecting crop MultiDisease.

• To use a transfer learning research framework for MultiCrop MultiDisease detection with real-world data.

• To assist farmers, by analyzing the real time parameters of crop and provide a robust and scalable Precise Decision Support System framework.

4. Research Methodology:

Crop multi-disease detection is an important task in agriculture for identifying and diagnosing various types of crop diseases. Crop multi-disease detection can be achieved using a variety of methods. The use of both deep learning and machine learning involves training models with labelled datasets to identify different kinds of crop diseases. Convolutional neural networks (CNNs), decision trees, support vector machines (SVMs), and other techniques can be used to train the models. The models are then tested on new data to determine how accurate and effective they are. The methodology used is determined by factors such as crop type, disease type, and available resources.

The steps listed below can be used to create such a methodology:

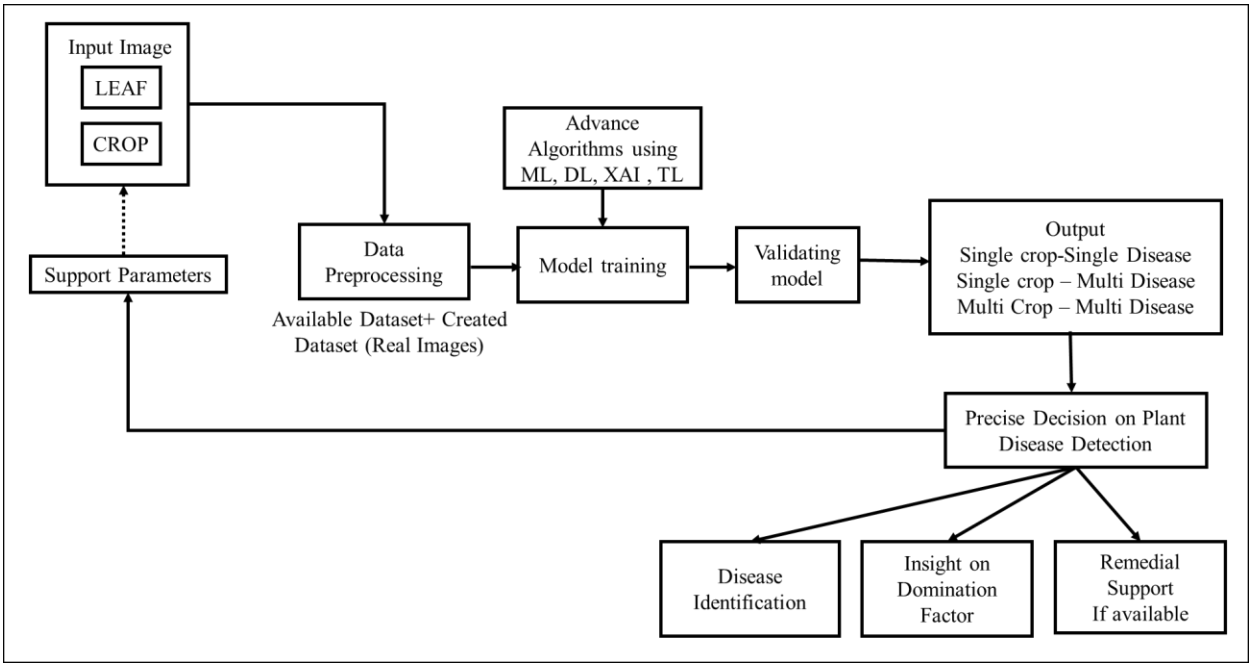

Figure 1: Precise Decision Support Framework for MultiCrop MultiDisease Detection

- **Data Collection:** The first step in developing a precise decision support system is to collect image datasets that include a diverse range of crops and diseases. The system requires a dataset of crop images that includes both healthy crops and crops affected by different diseases. These datasets can be obtained from different sources such as research institutions, government agencies, and real data from farmers. Collect and compile data of multiple crops, including images and information about the diseases that affect them.
- **Pre-processing:** Pre-process the data by removing irrelevant data and organizing the data set. Once the image datasets are collected, the next step is to annotate them by identifying

the crops and diseases present in each image. This can be done manually or through the use of automated annotation tools.

- **Model Training:** With the annotated datasets, machine learning , deep learning algorithms can be developed and optimized to accurately detect and diagnose multiple diseases affecting multiple crops in a single image or dataset. This can involve using different image processing techniques such as feature extraction and transfer learning algorithms to improve the accuracy of disease detection. Train a deep learning model using the pre-processed data set. The model should be able to identify and classify different diseases that affect multiple crops.
- **Validation:** Validate the model's performance by testing it on a separate dataset. It should be able to accurately identify the diseases.
- **Deployment:** Deploy the model to the target application, which could be a mobile app or a web platform. It should be able to take in images of the crops and identify the disease affecting them.
- **Maintenance:** Continuously monitor the performance of the model and make necessary improvements to ensure that it provides accurate and timely results.
- **Scaling:** As the number of crops and diseases increase, the model should be updated and upgraded to accommodate them. This could be done by adding more data and retraining the model.

Overall, developing a methodology for multi-crop multi-disease detection requires extensive data collection and pre-processing, model training, and deployment. The process needs to be monitored and maintained to ensure that the model provides accurate and reliable results. Multi-disease detection in crops can be a challenging task, as different diseases may have different symptoms and may affect the crop in various ways. However, there are several crop parameters that can be useful for multi-disease detection. Here are some examples:

- Leaf area: Measuring the leaf area can help detect changes in plant growth and can provide an early indication of disease development. Infected plants may have a reduced leaf area, while some diseases may cause an increase in leaf size.

- Chlorophyll content: Chlorophyll is essential for photosynthesis and is often affected by disease. Measuring the chlorophyll content can help detect changes in plant health and identify early signs of disease.
- Soil moisture: Soil moisture levels can affect plant growth and development, and changes in moisture levels can be an early indication of disease.
- Plant height: Changes in plant height can indicate changes in plant health, and monitoring plant height can help detect the presence of diseases.

These are just a few crop parameters that can be useful for multi-disease detection. Machine learning algorithms can be trained on these parameters to detect changes in crop health and identify the presence of multiple diseases.

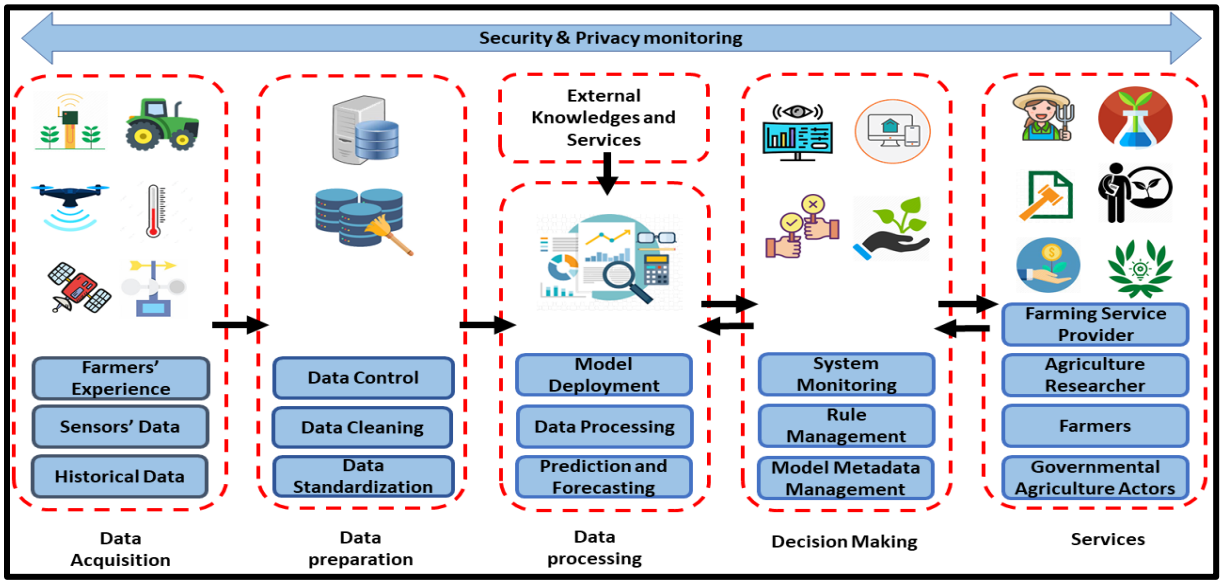

Figure 2: Decision Support framework in Digital Agriculture[23]

A Precise Decision Support system for MultiCrop MultiDisease detection can benefit greatly from two key technologies: Explainable AI and Transfer Learning.

Explainable AI refers to the development of AI models that can be easily understood and interpreted by humans. This is particularly important in decision support systems, where users need to be able to understand how the system arrived at its recommendations. By using explainable AI techniques, such as decision trees or rule-based models, the system can provide transparent and understandable results to users, making it easier to trust and use.

Transfer learning is a machine learning technique that allows models to learn from previous tasks and apply that knowledge to new, related tasks. By using transfer learning, a Precise Decision Support system can leverage pre-trained models on related crops and diseases to improve accuracy and reduce the need for large amounts of labeled data. This can lead to faster deployment of the system and better performance on new and emerging diseases.

Together, explainable AI and transfer learning can create a Precise Decision Support system that is both accurate and easily understood by users, making it a valuable tool for farmers and agricultural researchers alike**.**

Transfer learning is a machine learning technique that allows a model trained on one task to be re-purposed for another task. In the context of multi-crop multi-disease detection, transfer learning can be used to train a model on a large dataset of images that are not specific to a particular crop or disease and then fine-tune the model on a smaller dataset of images that are specific to the crops and diseases of interest.

The benefits of using transfer learning in multi-crop multi-disease detection are numerous.

- It allows for faster training times since the model is pre-trained on a large dataset.
- It can improve the accuracy of the model since it is leveraging knowledge learned from a larger and more diverse dataset.
- Finally, transfer learning can help to overcome the problem of limited data that is often encountered in agricultural applications, by allowing the model to learn from related tasks or domains.

Transfer learning is an important technique for multi-crop multi-disease detection that can help to improve the accuracy of the model and overcome data limitations.

Early detection of diseases in crops can prevent yield loss and minimize the use of pesticides. Transfer learning can be used to train deep learning models, such as CNNs, on images of healthy and diseased plants from different sources. The models can learn to distinguish between different disease symptoms and generalize to new crops and diseases with limited labeled data.

5. Scope of Research:

MultiCrop multi-disease refers to the occurrence of more than one disease in a crop. The scope of crop multi-disease is vast and can have significant economic, social, and environmental impacts.
Crop multi-disease can affect a wide range of crops, including fruits, vegetables, and ornamental plants and others. The impact of crop multi-disease can vary depending on the severity of the diseases, the timing of the occurrence, the susceptibility of the crop, and the available control measures.
The economic impact of crop multi-disease can be substantial, as it can reduce crop yields, quality, and marketability. This can result in significant losses for farmers and the agricultural industry as a whole. The social impact can be equally significant, as it can affect food security and the livelihoods of farmers and their families.
Furthermore, crop multi-disease can have environmental impacts as it can lead to the increased use of pesticides, which can have negative effects on the environment and human health.
Therefore, understanding the scope of MultiCrop MultiDisease and developing effective management strategies is crucial for sustainable agriculture.
Crop multi-disease research is an interdisciplinary field that focuses on studying the occurrence and management of multiple diseases that affect crops.

The scope of this research includes a wide range of topics, including:
Disease identification and characterization: The first step in managing crop multi-disease is to accurately identify and characterize the diseases that affect crops. This requires an understanding of the different symptoms, modes of transmission, and genetic makeup of the pathogens responsible for the diseases.
Disease ecology and epidemiology: Understanding the ecology and epidemiology of crop multi-disease is important for developing effective management strategies. This includes studying the factors that influence disease incidence and severity, such as environmental conditions, host susceptibility, and pathogen population dynamics.
Disease management: Crop multi-disease management involves a range of strategies, including cultural, chemical, and biological control methods. Researchers in this field study the efficacy of different management strategies and develop new approaches to control disease outbreaks.

Genetic resistance: Developing crops that are resistant to multiple diseases is a key area of research in crop multi-disease. This involves identifying genes that confer resistance to different diseases and developing crops that express these genes.

Emerging diseases: As new diseases emerge and existing diseases evolve, researchers in this field work to identify and characterize these diseases and develop effective management strategies.

Overall, the scope of crop multi-disease research is broad and interdisciplinary, requiring expertise in plant pathology, ecology, genetics, and agronomy. The ultimate goal of this research is to develop sustainable management strategies that protect crop yields and food security.

6. Hypothesis:

The development of a Precise Decision Support System for MultiCrop-MultiDisease Detection can significantly enhance the accuracy and efficiency of crop disease detection, leading to improved crop health and higher yields.

Developing an accurate and efficient decision support system for multi-crop and multi-disease detection can help farmers identify and treat diseases more effectively, reducing crop losses and improving yields.

The Precise Decision Support System for MultiCrop-MultiDisease Detection utilizes advanced technologies such as Transfer Learning, Explainable AI algorithms can accurately detect and diagnose multiple diseases affecting multiple crops in a single image or dataset, improving the accuracy of disease detection compared to traditional methods. The system can analyze various data sources such as images, weather data, soil data, and crop characteristics to identify patterns and correlations between crop diseases and their symptoms. As a result, farmers can improve crop health and yield, contributing to increased food security and sustainable agriculture practices.

7. Summary:

MultiCrop-MultiDisease detection is an important problem in agriculture that can greatly benefit from the use of advanced technologies like Explainable AI , Transfer Learning. MultiCrop-MultiDisease detection using transfer learning involves training a deep learning model to identify multiple crops and diseases using transfer learning techniques.

The following are the steps involved in building a multi-crop-multi-disease detection model using Advance technologies:

Collect and preprocess the data: The first step is to collect and preprocess the data. This step will need to gather a large dataset of images of crops and their diseases. It is important to have a diverse set of images to ensure the model can generalize well. Preprocessing techniques, such as data augmentation and normalization, can be used to increase the size of the dataset and improve the model's performance.

Transfer learning: The next step is to choose a pre-trained neural network and use it as a starting point for the multi-crop-multi-disease detection model. The pre-trained network is usually trained on a large dataset and has learned general features that can be useful for many computer vision tasks. By using transfer learning, the model can learn from the pre-trained network and quickly adapt to the new task.

Explainable AI: The system can give users transparent and understandable results by employing explainable AI techniques, such as decision trees or rule-based frameworks, which make it easier for users to trust and use the system.

Fine-tuning: The third step is to fine-tune the pre-trained network on the multi-crop-multi-disease detection task. Fine-tuning involves modifying the pre-trained network by replacing the last few layers with new layers that are specific to the new task. The new layers are then trained on the dataset of crop and disease images. The parameters of the pre-trained layers are frozen, while the new layers are trained. This way, the pre-trained network's general features are still useful, and the new layers can learn to classify crops and diseases.

Evaluation: The final step is to evaluate the performance of the multi-crop-multi-disease detection model. The model's accuracy, precision, recall, and F1 score can be calculated on a validation set. If the performance is not satisfactory, the model can be fine-tuned further, or a different pre-trained network can be used.

8. Future Scope:

The field of precise decision support systems for multi crop multi disease detection is a rapidly evolving and growing area of research, with many potential areas for future investigation. Some possible research scopes that could be explored in the future include:

- Incorporating more advanced image processing techniques: Taking images from different angles will provide more insight about crop disease allowing for more accurate and precise detection and diagnosis. Further research can be done to explore the potential of these techniques and how they can be incorporated into precise decision support systems.
- Developing more user-friendly and accessible systems: While precise decision support systems have shown promise in improving disease management practices, their adoption by small-scale farmers can be hindered by factors such as cost, complexity, and technical expertise. Future research can focus on developing more user-friendly and accessible systems that can be easily adopted and used by farmers with limited resources and technical knowledge.
- Conducting more comprehensive field trials: While field trials have been conducted to evaluate the effectiveness of precise decision support systems, further research can be done to conduct more comprehensive and long-term trials in a variety of working closely with farmers to implement the systems

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